Towards Reliability and Scalability in Feature Based Simultaneous Localization and Mapping

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Submitted in fulfillment of the requirement
for the degree of Doctor of Philosophy

2014

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Certificate

I, Gibson Hu, declare that this thesis entitled *Towards Reliability and Scalability in Feature Based Simultaneous Localization and Mapping* and the work presented in it are my own. I confirm that:

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- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself or jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

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Acknowledgements

Having come to the end of my PhD candidature, it has been a wonderful experience working with some of the best and brightest at the Centre for Autonomous Systems, UTS. Four years has passed by very quickly with much learning and research in the exciting field of Robotics. The road has been filled with many challenges, from late nights spent coding to traveling overseas for competition and conferences.

I have been very privileged to work with Associate Professor Shoudong Huang, Dr Alen Alempijevic and Professor Gamini Dissanayake, who have not only been inspirational but role models to me. I would also like to thank the post docs, Liang Zhao, Zhang Wang, Jack Wang, Gavin Paul and the students, Minjie Liu, Lei Shi, Andrew To, Kasra Khosoussi, Mohammad Norouzi, and Freek De Bruijn.

Finally, I would like to thank my friends and family for their unending support.

Abstract

Simultaneous Localization and Mapping (SLAM) has always been an attractive topic in the vibrant field of robotics. Feature based representations of the problem can be seen as one of the most common definitions. In recent years, many SLAM researchers have realized some limitations of filtering based methods and started to focus more on optimization based SLAM techniques. However, this raises several questions surrounding convergence reliability and, similar to filtering, algorithm scalability.

In SLAM, sensor noise and non-linearity often causes the problem to become difficult. Converging towards the global minimum in a non-linear least squares formulation is by no means easy. Typically, one would need to start from a good initial estimate, preferably already inside the basin of attraction of the global minimum. In this thesis, we introduce a technique called Iterative Re-Weighted Least Squares bootstrapping to achieve a good initial estimate even when the noise is exceptionally large.

As a robot continues to traverse through its environment the complexity of SLAM tends to scale badly with the cumulative nature of graph nodes and edges. To solve large SLAM problems within a reasonable time scale one must also take into consideration elements of accuracy and consistency. In this thesis, we propose two alternative algorithms to handle complexity, Sparse Map Joining and Pose Graph Representation. Both of which contain unique advantages for handling the diverse scenarios within SLAM.

A series of quantitative analyses are performed on a number of challenging datasets, both real and simulated. In addition to this we perform a comprehensive case study on a specific type of feature based SLAM problem, RGB-D SLAM. This demonstrates how our technique is capable of avoiding inaccuracies and failure scenarios that is otherwise common in other RGB-D SLAM algorithms.

Contents

1 Introduction **2**

1.0.1 SLAM Applications . . . 3

1.0.2 Brief History of SLAM . . . 4

1.1 Motivation . . . 5

1.2 Contributions . . . 6

1.3 Publications . . . 7

1.4 Thesis Outline . . . 8

2 Preliminaries **9**

2.1 Extended Kalman Filtering for SLAM . . . 9

2.2 Graph Based SLAM . . . 10

2.2.1 Odometry and Observation Information . . . 11

2.2.2 Linear Least Squares . . . 13

2.2.3 Non-Linear Least Squares . . . 15

2.2.4 Weighted Non-Linear Least Squares . . . 19

2.2.5 Least Squares for SLAM . . . 20

2.3 Front-End and Back-End . . . 21

2.4 Evaluating a SLAM algorithm . . . 22

2.4.1 Chi Squared (χ^2) . . . 22

2.4.2 Expected Value of χ^2 / Normalized χ^2 . . . 23

2.4.3 χ^2 Ratio . . . 24

2.4.4 Normalized Estimation Error NEES . . . 24

2.5 Related Works . . . 26

2.5.1 Improving Reliability 26
2.5.2 Overcoming Computational Complexity 28
2.6 Summary 30

3 Reliable Optimization **31**
3.1 Introduction 31
3.2 A General Framework for Reliable Optimization 32
3.2.1 Defining a Sequence 34
3.2.2 Iterative Re-weighted Least Squares 35
3.2.3 Formulation for IRLS 36
3.2.4 M-Estimators 38
3.2.5 Generalized Influence Function 40
3.2.6 Initial Influence 42
3.2.7 Stopping Condition for IRLS 42
3.2.8 Summary of IRLS algorithm 43
3.3 Evaluation Criteria 43
3.3.1 Benchmark Solution 43
3.3.2 Noise Conditions 43
3.3.3 Monte Carlo Evaluation 44
3.3.4 Success Rate 44
3.4 Experiment and Results 45
3.4.1 IRLS for Feature Based Graphs 45
3.4.2 IRLS on Pose Graphs 46
3.4.3 Resulting Maps 48
3.5 Discussion 50
3.5.1 Importance of Noise Correlation 50
3.5.2 Computation Time 50
3.6 Summary 51

4 Sparse Map Joining **52**
4.1 Introduction 52
4.2 Sparse Map Joining 53
4.2.1 Building Local Maps 53
4.2.2 Marginalization 54
4.2.3 Fusing Local Maps 55
4.2.4 SMJ Algorithm 58
4.3 3D Sparse Map Joining 59
4.3.1 Standard 3D Range and Bearing 59
4.3.2 SMJ for Bundle Adjustment(BA) 60
4.3.3 Dual-Observation Model Joining 61
4.4 Evaluation 63
4.4.1 Consistency using NEES 63
4.4.2 Accuracy using χ^2 Ratio 67
4.4.3 Computation Time 69
4.4.4 Resulting Maps 71
4.4.5 Real Datasets 72
4.5 Discussion 74
4.6 Summary 76

5 Pose Graph Representation **77**
5.1 Introduction 77
5.2 Pose Graphs 78
5.3 Pose Graph Representation of Feature Based SLAM 79
5.3.1 Obtaining Relative Pose 79
5.3.2 Information Reuse 81
5.3.3 Algorithm 86
5.4 Evaluation 87
5.4.1 Consistency using NEES 87
5.4.2 Accuracy using χ^2 Ratio 89
5.4.3 Resulting Maps 91
5.4.4 Computation Time 91

5.4.5 Real Datasets 94
5.5 Discussion 95
5.5.1 Further Improving Efficiency 95
5.5.2 Euler Angle Parameterization 96
5.5.3 Outliers in Feature Observations 96
5.6 Summary 99

6 Case Study: RGB-D SLAM 100

6.1 Introduction 100
6.1.1 Related Work 101
6.1.2 Motivation 102
6.1.3 Chapter Overview 102
6.2 RGB-D Cameras 103
6.3 Handling the RGB-D SLAM Front-End 106
6.3.1 Feature Selection 106
6.3.2 Feature Matching 107
6.3.3 Iterative Closest Point (ICP) 110
6.3.4 RGB Visual Odometry 111
6.3.5 Initializing a New Pose 111
6.3.6 Initializing a New Feature 111
6.3.7 Loop Closing 112
6.4 RGB-D SLAM 114
6.4.1 Flow Chart of RGB-D SLAM 115
6.4.2 Experiments and Results 116
6.5 Robust RGB-D SLAM 121
6.5.1 Local Map Building and Joining 121
6.5.2 Local Map Switching 121
6.5.3 Flow Chart of Robust RGB-D SLAM 124
6.5.4 Experiment 125
6.6 Discussion 129
6.6.1 RGB-D SLAM 129
6.6.2 Robust RGB-D SLAM 129

6.7 Summary 131

7 Conclusion and Future Work **132**

7.1 Summary of Contributions 133

7.1.1 Reliable Optimization 133

7.1.2 Sparse Map Joining 133

7.1.3 Pose Graph Representation 134

7.1.4 Case Study 134

7.2 Future Work 135

7.2.1 Improving the Reliability 135

7.2.2 Optimal Splitting Strategy 135

7.2.3 Finding the Optimal Subset of Key Poses 136

7.2.4 Issues in RGB-D SLAM 136

Appendix **138**

A Simulated Datasets 138

B Reliable Optimization 141

C Sparse Map Joining 142

C.1 Batch Optimization (BO) 142

C.2 Sequential Optimization (SO) 143

C.3 Divide & Conquer Optimization (DCO) 144

C.4 Sparse Map Joining Algorithm 145

D Pose Graph Representation 146

E Schur Complement 148

F Transforming between Rotation Matrix and Euler Angles 149

Bibliography **150**

List of Tables

3.1 Generalized function evaluation . . . 41

3.2 Pose/feature IRLS evaluation . . . 45

3.3 Pose only (Manhattan3500) IRLS evaluation . . . 47

3.4 Pose only (City10000) IRLS evaluation . . . 47

3.5 IRLS computation time evaluation . . . 50

4.1 Noise in simulated datasets . . . 63

4.2 Summary of simulated datasets . . . 63

4.3 SMJ 2D NEES evaluation . . . 65

4.4 SMJ 3D NEES evaluation . . . 66

4.5 SMJ 2D χ^2 Ratio evaluation . . . 68

4.6 SMJ 3D χ^2 Ratio evaluation . . . 68

4.7 SMJ computation time evaluation . . . 69

4.8 SMJ real data evaluation . . . 72

5.1 Summary of simulated datasets . . . 87

5.2 PGR 2D NEES evaluation . . . 88

5.3 PGR 3D NEES evaluation . . . 88

5.4 PGR 2D χ^2 Ratio evaluation . . . 90

5.5 PGR 3D χ^2 Ratio evaluation . . . 90

5.6 PGR computation time evaluation . . . 92

5.7 PGR real data evaluation . . . 94

5.8 Horn vs. Least Squares . . . 95

6.1 Feature extraction methods 106
6.2 Summary of simulated datasets 117
6.3 RGB-D SLAM results 117
6.4 RE-RANSAC failure modes 122

List of Figures

1.1 Home Robots . . . 3
1.2 Search and Rescue Robot . . . 4

2.1 Dynamic Bayesian Network . . . 10
2.2 Gauss-Newton vs Gradient Descent . . . 16
2.3 Front-End Back-End . . . 21

3.1 Graduated non-convexity . . . 33
3.2 Basic Sequence . . . 34
3.3 Weighted sequence . . . 36
3.4 Influence functions . . . 38
3.5 Weight functions . . . 39
3.6 Generalized function . . . 41
3.7 Pose feature result . . . 48
3.8 Pose graph (Manhattan3500) result . . . 48
3.9 Pose graph (City10000) result . . . 49

4.1 Local map marginalization . . . 55
4.2 Map joining . . . 56
4.3 Batch Optimization . . . 57
4.4 Sequential Optimization . . . 57
4.5 Divide & Conquer Optimization . . . 58
4.6 Dual-observation model joining . . . 62
4.7 SMJ simulation results . . . 71

4.8 SMJ real data results . . . 73

5.1 Pose/feature to pose graph . . . 79
5.2 Compute relative pose . . . 80
5.3 Single observation method . . . 82
5.4 Multi observation method . . . 83
5.5 Ignoring information reuse . . . 84
5.6 PGR simulation results . . . 91
5.7 Information matrix sparsity . . . 93
5.8 PGR real data results . . . 94
5.9 Outliers in the data . . . 97
5.10 Robust PGR results . . . 98

6.1 RGB-D Cameras . . . 103
6.2 RGB-D camera model . . . 105
6.3 FABMAP loop closing . . . 113
6.4 Flow chart for RGB-D SLAM . . . 115
6.5 Ground truth comparison . . . 119
6.6 Point cloud overlay . . . 120
6.7 Flow chart for RGB-D SLAM . . . 124
6.8 Visual odometry initial estimate . . . 126
6.9 Images at point of switch . . . 126
6.10 Optimized graph . . . 127
6.11 Point cloud overlay . . . 128
6.12 Point cloud overlay vs. architectural floor plan . . . 128

1 Circle trajectory . . . 138
2 Loop trajectory . . . 139
3 Manhattan features trajectory . . . 139
4 Sphere features trajectory . . . 140

Nomenclature

Formatting Style

$\hat{x}$	Measured
$\bar{x}$	Estimated
$\tilde{x}$	Actual

Subscript

m	features index	i, j	pose index
t	time index		

Superscript

$\mathcal{M}$	marginalized	P	pose set
F	feature set	O	odometry set
K	pose subset	L	local map
G	global map	S	sensor

Notations

$\sim \mathcal{N}$	normally distributed	$\underset{X}{\operatorname{argmin}}$	minimizer
$[.]$	vector elements	$\|\|.\|\|$	Euclidean norm
X^*	the optimum	$X^{(0)}$	initial estimate

Variables

$\mathcal{G}$	undirected graph	$\mathcal{V}$	graph vertices
$\mathcal{E}$	graph edges	E	essential matrix
Z	measurement vector	X	state vector
Σ	covariance matrix	Ω, Λ	information matrix
χ^2	chi squared value	ν	degree of freedom
$\mathcal{P}$	optimisation problem	w	weight scalar
F	fundamental matrix	S	scale
K	calibration matrix	T	transformation matrix

Functions

$g()$	pose to pose	$h()$	pose to feature
$b()$	generalized model function	$\rho()$	m-estimator
$Rot()$	rotation matrix	$Proj()$	projection matrix
$Horn()$	Horn's method	$\psi()$	influence function

Abbreviations

SLAM	Simultaneous Localisation and Mapping
ML	Maximum Likelihood
GN	Gauss-Newton
GD	Gradient Decent
PDL	Powell's Dog-Leg
LM	Levenberg-Marquardt
STD	Standard Deviation
SGD	Stochastic Gradient Descent
SBA	Sparse Bundle Adjustment
iSAM	Incremental Smoothing and Mapping
g^2o	General Graph Optimization
ParallaxBA	Parallax Angle Bundle Adjustment
Alg	Algorithm
RMSE	Root Mean Squared Error
NEES	Normalized Estimation Error Squared

IRLS	Iterative Re-weighted Least Squares
GT	Ground Truth
IMU	Inertial Measurement Unit
RPE	Relative Pose Error
ATE	Absolute Trajectory Error
SIFT	Scale Invariant Feature Transform
SURF	Speeded-Up Robust Features
I-SLSJF	Iterated Sparse Local Submap Joining Filter
EIF	Extended Information Filter
EKF	Extended Kalman Filter
SMJ	Sparse Map Joining
BO	Batch Optimization
SO	Sequential Optimization
DCO	Divide and Conquer Optimization
LAGO	Linear Approximation for Graph Optimization
TORO	Tree based netwORk Optimizer
MO	Multi Observation method
SO	Single Observation method
PGR	Pose Graph Representation
MAP	Maximum a Posteriori

DBN	Dynamic Bayesian Network
ICP	Iterative Closest Point
RE-RANSAC	Re-projection Error RANdom SAmpling Consensus
EM-RANSAC	Essential Matrix RANdom SAmpling Consensus
VO	Visual Odometry
FABMAP	Fast Appearance Based Mapping
IR	Infrared
M-Estimator	Maximum likelihood-type Estimator
GPS	Global Positioning System